# Unveiling the Lithology of Vegetated Terrains in Remotely Sensed Imagery

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Lithologic patterns within open canopy forests are revealed by selectively suppressing image contrasts attributable to variations in vegetative abundance.


## ABSTRACT

"Forced invariance" is a processing method that can subdue the expression of vegetation and enhance the expression of the underlying lithology in remotely sensed imagery. Data of each spectral band are altered in an empirically derived manner so as to produce a refined band that largely excludes contrasts attributable to variations in vegetation abundance. This is accomplished by (1) correcting the data for the effects of additive path radiance, (2) statistically characterizing the relationship between the band data and a vegetation index, and (3) multiplying the band data as a function of the index so that the average band value is generally invariant across all index values. Comparison of original and processed color composite displays confirms the method's utility in unveiling rock patterns consistent with nearby well-exposed bedrock and alluvial patterns downslope, especially in areas of open canopy vegetation such as in mixed arid and semi-arid terrains.


## INTRODUCTION

In areas of well exposed rocks, geological investigations readily benefit from the analysis of remotely sensed imagery for the differentiation of surficial lithologic materials. Variations in the abundance and type of iron-, carbonate-, and hydroxyl-bearing minerals (among others) result in differentiable spectra for differing rock types in the reflectance wavelengths, such as those imaged by Landsat Thematic Mapper

(TM). However, completely barren terrain is rare. Even in most arid regions, some spatially variable amount of vegetation covers the landscape and contributes its spectra (and shading) to the overall terrain reflectance, thereby obscuring the spectra of the underlying lithology. Siegal and Goetz (1977) and Murphy and Wadge (1994) have found that differentiation among rocks and among soils can be lost with vegetative covers of only 50 percent or less. Clearly, geological investigations can benefit from image processing methods that readily reduce the expression of vegetation, thereby unveiling lithologic patterns. This paper presents such methods.

Our approach, termed "forced invariance", subdues the expression of vegetation without requiring any knowledge of the lithologic composition of the scene prior to or during the de-vegetation process. During our processing, we are not (yet) trying to purify a hydroxyl signal and we are not (yet) trying to find the andesite. We do not require field data, laboratory analyses, or spectral libraries. Instead, our method simply removes the vegetation component of the signal in all bands so that the resultant refined bands can then be used for any of several objectives.

In contrast, most previous works in or related to vegetation suppression have had as their goal the mapping of one or more specified lithologic materials, and knowledge of the spectral characteristics of those and other materials has been required in order to complete the de-vegetation process. End products have included mineral abundance images, classification maps, or spectral indices. In short, previous works have generally required spectral characterization of lithologic materials and/or have produced image feature products rather than de-vegetated bands.

In the following sections, we provide overviews of previously reported approaches to de-vegetation image processing, provide and describe and evaluate examples of vegetation suppression via forced invariance, and then discuss the advantages (and limitations) of the approach.

## PREVIOUS APPROACHES

All approaches to de-vegetation image processing, including ours, are some form of spectral unmixing in its broadest sense. Here we divide the various approaches into two categories. One category we continue to call "spectral unmixing", to be consistent with previous literature. The other category includes previously unnamed methods that we group with our new methods under the generalized concept of "forced invariance".

Spectral unmixing generally requires detailed knowledge of the spectral signatures of materials known or assumed to be present in a scene plus models of how radiance from subpixel scene constituents combine into a single overall radiance measure (digital number, DN) for each pixel in each spectral band. Spectral unmixing can be implemented on a single pixel, and it can detect a constituent that is uniformly distributed across a scene.

Forced invariance requires no detailed knowledge of the spectral signatures of materials nor any complex mixing models. It utilizes scene statistics, so many pixels (usually a million or more) are required to implement this approach. Furthermore, it requires that the material to be suppressed (vegetation, in this case) be present in spatially variable amounts in order for that material's radiometric effects to be recognizable.

Below, we briefly describe previous work in spectral unmixing and in forced invariance . Interested readers are also referred to papers by Adams and Adams (1984) and Conel and Alley (1984) for additional approaches to vegetation suppression that are interesting in concept but are of limited applicability.

## Spectral Unmixing

Spectral unmixing is a procedure that determines the fractional abundance of each material within a mix of materials that can best account for the observed mixed spectrum at each pixel. It assumes that the overall reflectance of each pixel can be modeled as a combination of the reflectances of pure materials. If the spectral influence of each component is proportional to its abundance, then the spectral mixing is linear and can be modeled for each band as shown in Equation 1.

$$REF_{pixel} = (R_a F_a) + (R_b F_b) + \ldots R_n F_n \qquad \text{(Eq. 1)}$$

where $REF_{pixel}$ is the overall reflectance of the pixel, and R and F are the reflectances and fractional abundances, respectively, of the n various subpixel pure materials considered as possible constituents of the pixel. Pure materials are called "endmembers" because if all pure materials can be characterized spectrally, the spectra of all mixed image pixels must occur at positions intermediate to two or more pure materials in n-dimensional spectral space. Note that endmembers and their spectral properties must be determined prior to the application of these unmixing procedures. Endmembers are usually chosen and spectrally characterized by field surveys and radiometric analyses of samples, comparisons of image spectral signatures to existing spectral libraries, and/or analyses of the distribution of image pixels in n-dimensional spectral space.

Generally, shade is modeled as another linearly mixed scene component. Of course, shade is not a material object, nor is shading (variable irradiance) an additive component of terrain radiance. Thus, shading (and shadows) can pose significant problems for spectral unmixing.

The literature on spectral unmixing is fairly voluminous and dates back prior to the launch of Landsat 1 (Horwitz et al. , 1971). Smith et al. (1990) mentions the possibility of scaling non-vegetative endmembers to normalize them in regard to variable vegetation, and Mustard (1993) illustrates the use of non-vegetative endmembers (not bands) in color composite images. However, very few papers (e.g. Smith et al., 1988; Zamudio, 1992) even mention the use of spectral unmixing for the production of imagery that is vegetation-free but not convolved into endmember products.

Bierwirth (1990) provides the clearest example of using spectral unmixing for the de-vegetation of image bands (similar to our objective). In fact, this is the only example that we could find where this objective was stated, the procedure was described, and the results were well illustrated. Using NS-001 airborne scanner data, Bierwirth derived abundance images for each of several materials. He then recalculated brightness values in the original bands with both green and dry vegetation removed by (1) proportionally rescaling the remaining (lithologic) fractional abundances so that they would total 100% and then (2) recalculating pixel values using Equation 1. Comparable before-and-after color composite images were presented that show apparent suppression of at least the green vegetation fraction. Dry vegetation is less recognizable in the "before" image, rendering evaluations of its removal more difficult. A "vegetation index" ratio image (comparable to TM ratio 4/3) of the de-vegetated bands was shown to have a residual pattern matching that of hematite, as might be expected of successful results, and it was quite dissimilar to the original vegetation index image, again indicating success.

**Forced Invariance in Band Ratios**

Methods that we henceforth call "forced invariance" include and expand upon a concept derived by Elvidge and Lyon (1985a). In simple terms, forced invariance calculates images that are invariant relative to a specific spectral index. Features represented by that spectral index will not appear in the resultant images because those features will contribute no variance.

Elvidge and Lyon, using field spectra and airborne scanner imagery, noted a near-linear trend among pixels of variable vegetation amount in plots comparable to TM band ratio 5/7 versus TM band ratio 4/3 (1.65µm / 2.22µm versus 0.83 µm / 0.66 µm, respectively). TM ratio 4/3 (a common "vegetation index") is very sensitive to vegetation amount and relatively insensitive to lithologic variation. TM ratio 5/7 generally varies with the abundance of hydroxyl-bearing minerals (as well as carbonate and some other minerals).

However, TM 5/7 is also variable with vegetation amount and can therefore be difficult to interpret. The linear trend in the ratio-versus-ratio plot clearly related to variable vegetation abundance. Consequently Elvidge and Lyon deduced that deviations from the trend line should be invariable with vegetation amount and would therefore be vegetation-free measures of lithologic variations in the 5/7 ratio.

Fraser and Green (1987) describe an implementation of the concept of Elvidge and Lyon that uses no field data. Variation in vegetation amount is assumed to be so statistically dominant in the image data that the first principal component of the two ratios closely corresponds to the vegetation trend. The second principal component then measures lithologic variations independent of vegetation. Fraser and Green express caution about this assumption, and in our experience, we find this assumption to be unreliable, particularly for scenes that have localized concentrations of vegetation but are otherwise very barren, such as in the arid southwestern United States. Our solution, which can work very well, is to base the processing statistics on only those pixels above some reasoned threshold in the 4/3 ratio. This assures that statistical relationships are dominated by vegetated pixels. Such thresholding is usually needed whether using the principal components approach or our alternative approach, as described later.

Evaluation of the results of Elvidge and Lyon (1985a) and Fraser and Green (1987) lies mainly in the comparison of their de-vegetated 5/7 ratio image to their 4/3 ratio image. Ideally, these two greyscale images should differ greatly in appearance and should have statistical correlation near zero. Elvidge and Lyon provided favorable image comparisons (but not the correlation measure), and also provided confirming evidence in the form of comparative image and terrain spectral transects. Fraser and Green provided only image comparisons, but the processed image distinctly showed successful suppression of at least the most prominent vegetation pattern.

## FORCED INVARIANCE IN BAND RATIO COLOR COMPOSITE DISPLAYS

Here we show that the concept of Elvidge and Lyon can be extended to additional band ratios, and that these ratios can be combined into color composite displays, which are vastly superior to greyscale images for the visual discrimination of lithologic materials. Rowan et al. (1992) similarly transferred the Elvidge and Lyon concept to an additional band ratio (TM 4/5) but not with the objective of generating color composite imagery.

Evaluations of the success of the de-vegetation process itself likewise benefit from the use of color composite displays. Vegetation is commonly distinctive in both spectral appearance and geographic distribution prior to the processing. Its appearance and "disappearance" (and the unveiling of distinctive lithologic patterns) is far more convincing in three-dimensional color space (millions of colors) than on a one-dimensional greyscale (256 levels of grey).

The image data used here is a Landsat TM scene of south-central Nevada, 180 km north-northwest of Las Vegas, covering parts of Lincoln and Nye Counties, including the community of Rachel (Figure 1). (Landsat Path 40, Row 34; Latitude 37º 40'N, Longitude 115º 40'W; taken on 4 November 1986.) The region is arid to semi-arid. Valleys consist of broad alluvial fans having low density sagebrush and dry lakes having little, if any, vegetation. The mountain ranges are mostly rugged and have vegetation densities that generally increase with elevation, climaxing in a juniper-pinyon woodland at the higher elevations (Figure 2). The geologic setting includes plutonic and volcanic rocks, as well as carbonates and other sedimentary rocks, and has been described by Tschanz and Pampeyan (1970) and by Howard (1978). This site was chosen for testing and demonstration purposes because its lithology is diverse and spectrally distinct, such that de-vegetation procedures should reveal terrain having a clear lithologic pattern.

Our computational approach differs from that of Fraser and Green. It can be equivalent in result, but it uses statistics that more directly target the objective. First, we take the logarithm of all ratios (including the vegetation index) so as to linearize any exponential relationships that may exist among them (relationships that were already linear will remain linear). Then, instead of fitting principal components to the vegetation index (TM ratio 4/3) and the ratio of interest, we iteratively perform a weighted linear mixing of those two ratios until we find the result that has minimal correlation with the vegetation index. In other words, if the ratio image of interest is positively correlated with vegetation we "subtract some vegetation image" from it. If the ratio image of interest is negatively correlated with vegetation we "add some vegetation image" to it. The concept is that an image that has no correlation with vegetation abundance is generally invariant with vegetation abundance and is therefore unlikely to significantly depict vegetation.

Figures 3A and 3A' depict "before" and "after" ratio-based de-vegetation processing for our test scene. Landsat TM band ratios 3/1, 5/4, and 5/7 are depicted in blue, green, and red, respectively. (Ratio 3/1 generally varies with ferric iron, ratio 5/4 generally varies with ferrous iron, and ratio 5/7 generally varies with hydroxyl-bearing and carbonate minerals.) Each ratio has been multiplicatively merged with band 4 in order to return topographic shading (and some albedo information) to the scene achromatically. This helps facilitate recognition of physiographic context and geologic structure. This method of merging three colored (chromatic) components and an uncolored (achromatic) component is termed "four components processing" and is described by Crippen (1988, 1989). Band 4 is used here as the achromatic component because it is the band having the least correlation with the vegetation index. (Natural vegetation appears generally darker than barren rocks in all bands for this scene, but it is least dark in band 4). Band 4 therefore returns shading to the scene while only minimally returning the depiction of vegetation, and even then only as subtle brightness patterns.

In the "before" image (Figure 3A), vegetation appears reddish-magenta. It is relatively bright in red (TM 5/7), dark in green (TM 5/4), and neutral in blue (TM 3/1). This is also evident in Figure 4, which plots each ratio versus the vegetation index (TM 4/3). Clearly, TM 5/7 values increase, TM 5/4 values decrease, and TM 3/1 values are generally invariable with increasing vegetation amount as measured by the vegetation index.

In the "after" image (Figure 3A'), vegetation in the mountains has largely vanished because ratio values are generally invariable with variable vegetation amount. Note that the processing has not just masked the vegetation pattern. It has revealed the lithologic pattern where it had previously been obscured by the vegetation. Lithologic features appear continuous between naturally exposed and "newly exposed" areas. Also, de-vegetated source rocks in the mountains have the same spectral appearance as the detritus that has washed out of the mountains to the naturally exposed alluvial fans. De-vegetation via forced invariance is very effective on this scene.

Let us reiterate the concept of our approach to de-vegetating band ratios. We linearly and iteratively mix each selected band ratio with the vegetation index until the result has zero correlation with the vegetation index (using logarithms of the ratio and index). We do this under the assumption that images that have no correlation with the vegetation index will be generally invariable with vegetation amount and are therefore unlikely to depict vegetation. This "forced invariance" approach appears to work very well. Might a similar approach be applicable not just to band ratios, but to bands?

## FORCED INVARIANCE IN BAND IMAGERY

### Concepts and Deriving the Procedure

In order to design an algorithm to make vegetation "disappear" in image bands, we need a fundamental understanding of how and why vegetation originally appears in a band image. This discussion will expand upon and serve to clarify concepts presented in previous sections.

Detection and identification of any feature in an image relies upon recognition of its color, size, shape, texture, pattern, height, shadow, and/or spatial relationship to other features (Estes et al., 1983). Ultimately, however, all of these feature characteristics require *contrasts* in tone. If an image loses all contrast, all features in it cease to be seen because all of these feature characteristics cease to exist.

It follows then, at least in concept, that our task becomes simple. Question: How can we selectively make only vegetation disappear? Answer: Selectively eliminate only its contrast. Our method is based on this postulation.

In a vegetated scene, every pixel in every band has a DN value. If that same scene had no vegetation cover, every pixel in every band would still have some DN value. This is obvious, but it serves to remind us that the only differences between vegetated and de-vegetated scenes are increases or decreases of some of the DN values of individual pixels in individual bands. Implementing the correct changes will force the vegetation to disappear. Thus, fundamentally, in order to de-vegetate a scene we must develop some logic as to how much to increase or decrease (if any) the DN value for each pixel in each band.

Intuitively, in simple terms, we need to know two things:

(1) What amount of vegetation is there in each pixel?

(2) How strongly and in what manner (darkening or brightening) does any particular amount of vegetation affect pixel radiance in each band?

Fortunately, a calibrated physical measure of item (1), the amount of vegetation (e.g. biomass, leaf area, or land cover percentage), is not needed. Instead, we simply need some relative measure of the prominence of vegetation in terms of its radiometric impact. An uncalibrated vegetation index serves this purpose. The ratio of near-infrared (0.76-0.90 μm) radiance versus red (0.63-0.69 μm) radiance (e.g. Landsat TM band ratio 4/3) is effective as a vegetation index because it varies much more with vegetation vitality (abundance and vigor) than with variations in lithologic variables (e.g. iron concentrations). Thus, a vegetation index tells us, in an appropriate relative manner, the "amount of vegetation" in each pixel.

Item (2), how vegetation affects pixel radiance in each band, is certainly a complicated issue (and will be addressed further in the Discussion section below). However, the image data itself can tell us the general relationship between vegetation amount and band darkening or brightening. This relationship is evident in plots of band DN values versus the vegetation index (e.g. Figure 5, top).

Forced invariance uses the assumption that the general relationship between vegetation amount and band darkening or brightening is applicable to all pixels. This will be an erroneous assumption for some pixels and may be an inadequate assumption for some scenes. However, it is an adequate and useful assumption for at least some scenes, as will be self-evident in our results, and it leads to a simple de-vegetation procedure.

Remember that our method is based on the postulation that eliminating image contrasts related to vegetation will eliminate the appearance of vegetation in the scene. What this means is that we seek to alter the image data so that variable amounts of vegetation will not (in general) affect pixel DN values.

If we assume:

(1) that the distribution of vegetation across the terrain is independent of rock type (i.e. geobotanical relationships, if any, do not significantly influence the band DN versus vegetation index relationships),

(2) that rock albedo is not by chance substantially correlated with vegetation amount (e.g. bright rocks and dense vegetation do not both occur together at high elevations for unrelated reasons, such as erosional resistivity and air temperature), and

(3) that the distribution of vegetation is not strongly related to terrain shading and shadowing (at the particular sun azimuth and altitude present during image acquisition),

then we should expect that DN averages (and, ideally, DN variances) should not vary significantly with the vegetation index after completion of the de-vegetation process.

So, how do we change original data distributions (as seen in Figure 5, top) to "de-vegetated" (vegetation invariable) data distributions (as seen in Figure 5, bottom)? The following two reasonable constraints point the way to a simple procedure.

(1) The mean DN value should become reasonably uniform across all vegetation index values.

(2) DN values corresponding to dark pixels (pixels of zero terrain radiance, whether present or not) should remain (or become) reasonably uniform across all vegetation index values.

Constraint (1) is the primary objective for the removal of image contrasts related to vegetation amount. Constrain (2) is necessary for maintaining radiometric integrity.

The procedure thus becomes evident. Dark pixel DN values should be determined and set to zero via subtraction, and then all pixels at each vegetation index level should be multiplied by a factor that sets their mean to a target DN value. (The factors vary with the vegetation index, but the target DN does not.) In other words, apply dark pixel corrections, then multiply all pixels in each vegetation index column of

Figure 5, top row, by an amount that flattens the data trend line so that it appears as in Figure 5, bottom row. Note that the multiplicative step will not alter the corrected dark pixels because zero times anything is still zero.

Dark pixel corrections suppress atmospheric path radiance (the sensor observed brightness of the atmosphere) plus the sensor calibration offset of each band. In other words, they are the DN values for zero-reflectance terrain (whether or not it exists in a scene). Especially in rugged terrain, they are required in order to exclude terrain shading distortions from band ratios, including the vegetation index image used in forced invariance (see Crippen, 1988a, for an illustration of this effect). Thus well chosen dark pixel corrections, commonly called "atmospheric corrections", can be critical at two stages of the de-vegetation process. (Dark pixel values for the Rachel, Nevada, TM scene are 41, 10, 6, 1, 0, and -1 for bands 1, 2, 3, 4, 5, and 7, respectively.)

## Procedure Summary

In simple terms, these are the steps used to de-vegetate bands of a multispectral scene via forced invariance:

(1) <u>Estimate dark pixel DN values for each band and subtract them from all pixels of each band image</u>. (Crippen (1987) describes various methods of estimating dark pixel values.) Use the resultant band images in all subsequent steps, including calculation of the vegetation index.

(2) <u>Calculate a vegetation index</u>. A simple ratio of the near infrared band versus the red band (e.g. Landsat TM band ratio 4/3) serves this purpose. The vegetation index image may be scaled, quantized, and stored as integers from 0 to 255, with minor high and low saturation. (Scaling information can be discarded, and the choice of a log ratio index versus a simple ratio index is inconsequential to the results.)

Then for each band (as described in graphical terms):

(3) Plot DN values versus vegetation index values. In other words, gather statistics relating band DN values to vegetation index values, as graphically represented in Figure 5, top row.

(4) Fit a smooth best-fit curve to the plot. Essentially, this means finding the average DN value at each scaled and quantized vegetation index value (or group of values), but then also smoothing the results over several quantized vegetation index values.

(5) Multiplicatively flatten the curve and drag all the pixels along with it. Select a target average DN value (e.g. 64) and multiply all pixels at each vegetation index level by an amount that shifts the curve to that target. In other words, for each vegetation index level, multiply all pixels at that vegetation level by the target DN divided by the curve DN. Saturate any pixels that exceed the upper quantization limit (e.g. 255).

## Results

Figures 3B and 3B' demonstrate band de-vegetation by forced invariance for our test scene. Landsat TM bands 1, 4, and 7 are displayed in blue, green, and red, respectively. As is typical, vegetation appears green with this band and color assignment combination after the scene is contrast stretched and color balanced. After forced invariance, the vegetation is suppressed and the lithologic pattern is more clearly revealed. Additionally, the "after" image benefits from contrast stretching and color balancing being applied only to the lithologic features.

In general, carbonate rocks appear blue, granitic rocks appear green, and volcanic rocks appear pink in Figure 3B'. Note that as with the band ratio example, there is good continuity between naturally exposed rocks and rocks revealed by the processing, as well as between revealed source rocks and naturally exposed rocks downstream on the alluvial fans.

## DISCUSSION: THE METHOD

### Dark Pixel Corrections

Why are dark pixel corrections needed? Firstly, they are needed to produce a useful vegetation index image. The vegetation index is a band ratio intended to represent the ratio of terrain reflectances. However, radiance recorded by a sensor includes several terms other than terrain reflectance. Some are multiplicative terms (atmospheric transmissivity, sensor gain, topographic shading) and some are additive terms (atmospheric path radiance and sensor calibration offset). If the additive terms can be estimated and removed, then ratioing will reduce the non-reflectance multiplicative terms of recorded radiance to a constant (they "divide out") as long as they are invariable or proportionally variable across the scene between the ratioed bands. Dark pixel values correspond to the sum of the additive terms of recorded radiance (those that do not "divide out") and therefore represent the DN corrections needed to allow band ratioing to produce images that are representative of the ratios of terrain reflectance.

Secondly, dark pixel corrections are needed to maintain radiometric fidelity of the de-vegetated bands. Pixel DNs get multiplied by a variable factor in the de-vegetation process. Clearly, pixels of zero terrain radiance (whether real or theoretical) should retain a uniform DN value. Zero is the only DN value that remains invariable when multiplied by a range of numbers. Dark pixel corrections (estimating and subtracting dark pixel DNs from all pixels) therefore helps to maintain the radiometric fidelity of the de-vegetated images.

## The Vegetation Index

We use a simple ratio of the near infrared (NIR) band versus the visible red band for a vegetation index. Such a ratio has long been recognized as a general measure of vegetation abundance (Jordan, 1969). Visible red light is strongly absorbed by chlorophyll, while near-infrared insolation is highly reflected by plant leaves because of internal leaf scattering and no absorption (Knipling, 1970). No such extreme reflectance/absorption differences occur for lithic materials over these wavelengths, and NIR/Red ratios for rocks are far lower than those for foliage. In fact, NIR/Red ratios for foliage are distant outliers relative to the range of NIR/Red ratios observed for rocks. Consequently, variations in NIR/Red ratios in a scene having vegetation are dominated by variations in the abundance of that vegetation.

Band ratios have been shown to be imperfect measures of vegetative abundance for plants growing upon rocks and soils of variable albedos (Elvidge and Lyon, 1985b), and alternative vegetation indices have been proposed, primarily for use in agricultural research (e.g. Richardson and Wiegand, 1977). However, when used with dark pixel corrections, band ratios should be superior to those alternatives in suppressing topographic shading effects, which is the greater concern at many sites of geologic interest.

## Fitting, Smoothing, and Flattening the Curve

Plots of band data versus a vegetation index, such as those in Figure 5, top, can have substantial irregularities. Pixels are not distributed evenly across all index values because (1) pixels at each vegetation amount are unlikely to be present in equal numbers in a scene, and (2) some ratio values are impossible for shaded pixels (and other pixels) having low integer DN values (e.g. $131 / 107 = 1.2243$, but smaller integers cannot produce the same ratio value), as is evident in the data distribution patterns of Figures 4 and 5. Some index values will therefore have (1) an insufficient statistical sampling and/or (2) a bias toward high DN values. These are issues to consider when fitting a curve to these data plots.

Clearly, we cannot simply define the curve by "connecting the dots", where each dot is the average DN at each quantized index value. Some smoothing of the curve is needed. Various spline fitting routines may be applicable. However, we have found that boxfiltering the data with median and mean filters readily provides a fitted curve that appears reasonable. We would expect a "reasonable" curve to be smooth and to not have more than one change of direction (brightening or darkening) over the range of vegetation index values.

In the example shown here (Figure 5, top), DN values for each band continuously decrease with increasing vegetation index value. This is likely due to shadowing of the ground by plants being the dominant radiometric effect of increasing vegetation amount. In some scenes, DN values decrease and then increase with increasing vegetation index values, particularly in TM band 4. This probably indicates that vegetation reflectance is generally greater than lithologic reflectance in that band, but shadowing is still the dominant effect (resulting in net pixel darkening) until vegetation grows thick enough to close its canopy and hide the shadows, at which point reflectance dominates (resulting in net pixel brightening). Other possibilities may also occur.

The filters we have used were chosen inferentially. We have made no attempts to optimize them because they appear to work well on a variety of scenes. First we tabulate the band DN values by vegetation index level (a 256x256 array). Then we find the median of all data (individual pixels) occurring within 5 quantization levels of each vegetation index level (0-255) and store those medians as a 256-member array. Next we filter that one-dimensional array several times to smooth it. First we sequentially use median boxfilters of half-widths 11, 7, 3, and 1. Then we sequentially use mean boxfilters of half-widths 1, 5, and 9. The median filters tend to avoid outliers, while the mean filters tend to smooth stair-steps. The filters are not allowed to reflect nor truncate against the ends of the array, which could distort the curve trends there. The larger filters smooth more, and the smaller filters reach closer to the array ends. Because the array ends may be insufficiently smoothed, we plot and observe the curve and then allow an option to replace the ends with user selected extrapolations from the adjoining curve segments.

The curve represents the general relationship between vegetation amount and pixel darkening or brightening. If it were flat, it would indicate that vegetation contributes no contrast to the band image. By flattening it, we seek to remove image contrast attributable to vegetation. As previously indicated, the flattening procedure is simple. Choose a target average DN value for the entire band, then multiply all pixels at each vegetation index value as follows:

$$\text{Pixel DN}_{new} = \text{Pixel DN}_{original} \times (\text{Target DN} / \text{Curve DN}_{veg\ index}) \quad \text{Eq. 2}$$

This flattens the curve and multiplicatively shifts all pixels at each vegetation index level by a constant factor. Note that the DN change ($DN_{new} - DN_{original}$) is proportional to the original DN for each pixel at any given index level.

**Problematic Image Features: Radiometric Outliers**

As noted previously, our procedures assume that geobotanical, physiographic, and coincidental relationships between vegetation distribution and non-vegetative terrain radiance do not greatly affect the image statistics used in forced invariance. Clearly, this assumption can run into problems. Fortunately, where these problems are most severe, there is often a simple solution.

For example, playas (dry lakes) are present in the Landsat TM scene we show here. The playas are barren of vegetation and consequently have the lowest vegetation index values. Meanwhile, they typically have highly anomalous DN values in most bands. As radiometric outliers, they are incongruous with the general relationship between terrain brightness and vegetation amount that we seek from the image statistics and are therefore problematic.

The solution is to exclude the playas from the compiled statistics. This is accomplished by creating a binary mask that isolates the playa pixels, usually by thresholding and visually editing the band in which the playas are most highly anomalous. The mask is then used to nullify the playa pixels during compilations of image statistics. Similar procedures can be used to mask other radiometric outliers, such as water, clouds, snow, and (as we have found in this scene) cultivated vegetation.

Forced invariance based upon masked-image statistics is then applied to the entire image, including any playa, water, cloud, snow, and crop pixels. The pixels that were excluded from the statistics are brightened or darkened an amount that is proportionally equal to that for other pixels having similar index values.

**Notes on the Radiometric Outliers of This Scene**

The cultivated vegetation of our test scene lies just west of the community of Rachel, Nevada, and appears as pivot-irrigated circular fields (of alfalfa). Note that pixels for these fields are anomalously bright in all bands at any given vegetation index level as compared to natural vegetation (Figure 5). This is due to differences in plant shadowing and reflectance as compared to the natural vegetation. These crops were masked while deriving image statistics and are over brightened (Figures 3B' and 5) by band processing designed specifically to suppress natural vegetation.

Playas and cultivated vegetation ("crops") appear differently between the 'before' and 'after' ratio-processed imagery (Figures 3A and 3A', respectively), however this is in part due to the display processing and not just the de-vegetation processing. Remember that these features were excluded from statistics used for the de-vegetation process yet were subject to processing based upon those statistics. Also remember that these band ratio color composites are multiplicatively merged with band 4, which generally improves image interpretability. In the 'before' ratio composite prior to merger with band 4 (not shown), both the playas and the crops appear reddish magenta as expected. However, playas are extremely and anomalously bright in band 4 and become the brightest features in the scene after the merger with band 4. Consequently, the playas become saturated (truncated at DN=255) in all channels after contrast stretching optimized for all other features. In the 'after' ratio composite prior to merger with band 4 (not shown), playas appear reddish magenta, thus retaining their chromaticity (as we would desire for exposed lithology). However, crops are not adequately suppressed by statistics based specifically on natural vegetation, and they remain anomalously high in band ratio 5/7, become anomalously high in band ratio 5/4, and remain fairly neutral in band ratio 3/1. The result is that crops become a bright and unsaturated yellow ("unsaturated" in the chromatic sense) prior to merger with band 4, and remain brighter than even the playas after merger with band 4, allowing the playas to retain their chromaticity (reddish magenta) after contrast stretching of the final display.

## DISCUSSION: GENERAL CONSIDERATIONS

### Vegetation's Effect on Pixel Brightness

The effects of vegetation on pixel brightness can be complicated and diverse on a pixel by pixel basis. In general, in each band, vegetative matter will have a differing reflectance than its lithologic host, plus it will cast shadows that darken parts of the pixel that it does not cover. Differing species will have differing reflectance spectra and will project differing shadow lengths and depths. Self shadowing will also vary among species.

Where vegetation is tall, narrow, and sparse, the shadowing effect may dominate, especially with low sun angles, because a plant's shadow may cover a greater area of the pixel than the plant itself. The shadow will always darken the pixel regardless of the reflectance properties of the soil or bedrock.

Where vegetation is short but dense, or sun angles are high, cast shadows may be small relative to the area covered by the plant itself. In that case, reflectance contrasts may be the dominant effect and pixels may brighten in some bands with increasing vegetation amount, particularly over dark substrate. Indeed, equivalent types and amounts of vegetation may darken a bright substrate and brighten a dark substrate.

There will always be some range of reflectances for lithologic materials, as well as some diversity of radiometric effects imposed by the vegetation. On a pixel by pixel basis, these effects are not fully determinable based on image data alone. Our simplifying assumption models the effect of each amount of vegetation in each band as a multiplicative constant (indicated by a point on a best-fit curve). If a given amount of vegetation can darken bright rocks, and that same amount of vegetation can brighten dark rocks, clearly our model has shortcomings. The model will likely work best where shadowing is the dominant effect of vegetation since shadows always darken rocks of any brightness. That our simple model is adequate and useful for at least some scenes is well demonstrated by the results shown here in our example.

## The Data Trend Concept

We use the term "forced invariance" because we are forcing the processed image to be invariable with vegetation amount (i.e., normalized relative to vegetation). The ratio-versus-ratio procedures of Elvidge and Lyon (1985a) and Fraser and Green (1987) are a form of forced invariance. If the trend of variable vegetation amount is approximately linear in ratio-versus-ratio space, then measurements perpendicular to that trend will be largely independent of that variation. This does not mean that trends for other materials will be perpendicular to the trend for vegetation, nor that they need to be perpendicular in order to be measured independent of vegetation.

Fraser (1991) attempted to separate vegetation and iron concentrations in TM ratios 4/1 and 3/1 using principal components. He noted that if the data variance is *dominated* by the vegetation, PC1 (the first principal component) will follow the vegetation trend and PC2 will measure iron concentration, whereas if the data variance is *dominated* by the iron concentration, PC1 will follow the iron trend and PC2 will measure vegetation. This is true, but if the two trends are not orthogonal (and they are most likely not), then how does one use principal components to isolate iron concentrations if iron dominates image variance? In that case, PC1 will follow the iron trend, but will not be orthogonal to (and will therefore not be invariable with) vegetation. And what does one do if neither material dominates image variance? The principal components may be orthogonal to neither data trend and will isolate nothing.

The key to removing the effects of vegetation from band ratios is to identify the vegetation trend and (assuming it is linear) re-measure the data perpendicular to it. If the trends of other materials are orthogonal to the vegetation trend, great. But if not, then the method still works. The variance of those materials gets re-scaled by the cosine of the deviation from the orthogonal. Since ratios are unitless quantities, that re-scaling is largely irrelevant, except in relation to how the data and ratios have been quantized previously (and other data noise issues).

In de-vegetating bands instead of ratios, we again use TM ratio 4/3 to measure vegetative effects on spectral data. However, there is no linear vegetation trend in band-versus-ratio space, and the units of band data (radiance) do not match those of band ratios (unitless). Thus our approach is to create (or "force") a vegetation trend that is orthogonal to the band axis. The band axis will then, conversely, be orthogonal to the vegetation trend, which meets our conceptual objective.

**Contrast Stretching and Color Balancing**

As seen in our examples, forced invariance can be highly effective in spectral unmixing. Pixels that have both lithologic and vegetative information can be refined to show only the lithologic information, allowing us to "see through" the forest. But what happens to pixels that are fully vegetated? If the forest is "removed" and that's all there was, then what will those pixels look like?

Remember that image features are seen as contrasts (variable greys or colors). Vegetation suppression by forced invariance selectively removes the contrast between vegetation and other image features. The result is that areas with dense vegetation tend toward neutral (and may be noisy because most of the radiometric signal is suppressed). By "neutral" we mean that they will tend to take on the average DN value in each band (the "target" value used in our procedure) and that in a three-band display they will tend toward the overall color of the refined scene. Topographic shading will remain, as will any image features (vegetative, lithologic, or otherwise) that are unrelated to, or not fully characterized by, the vegetation index.

By removing obstructive vegetative patterns, especially where they dominate scene variance, non-vegetative features more fully benefit from image contrast stretching. This is somewhat analogous to spatial filtering. Subtle detail is often obscure in scenes having bimodal, higher variance regional contrasts. High-pass filtering suppresses the regional contrasts so that image contrast stretching is beneficially applied only to the detail. Forced invariance can work similarly, except instead of suppressing certain spatial frequencies, it suppresses certain image features. The features that remain then benefit from contrast stretching that is unencumbered by scene variance unrelated to the features of interest.

Likewise, vegetation suppression via forced invariance allows color balancing to become unencumbered by scene variance that is unrelated to the features of interest. Scenes that depict widespread vegetation in green often depict everything else in magenta (the chromatic complement of green) because the vegetation-versus-everything-else contrast is great and statistically dominant. By suppressing the vegetation pattern, the remaining image features will spread across the chromatic gamut when all display channels are contrast stretched. The result is greatly improved discriminability of the features of interest.

## CONCLUSIONS

Forced invariance is a means of enhancing multispectral remotely sensed imagery for lithologic interpretation by suppressing the expression of the overlying vegetation cover. It is based on the fundamental concept that features must have contrast in order to be seen in an image. Vegetation can be forced to disappear from a scene by selectively subduing its contrast.

As demonstrated, the method is particularly effective for imagery of areas of open canopy forest (and little understory) because a significantly strong lithologic signal will remain after the vegetation signal is suppressed. In areas of closed canopy, we find that the method can still be beneficial because vegetation is typically a statistical spectral outlier that interferes with image contrast stretching and color balancing. By neutralizing image contrast related to vegetation abundance, lithologic discrimination is maximized.

The forced invariance method should be applicable to the suppression of any image feature for which an index image can be generated. Snow is spectrally distinct, and we have successfully suppressed its expression in Landsat TM imagery by methods identical to those described here by using band ratio 3/5 as a snow index. Index images derived from higher dimensional spectral data sets and perhaps even non-spectral data sets may open new opportunities for the forced invariance approach to image information enhancement.

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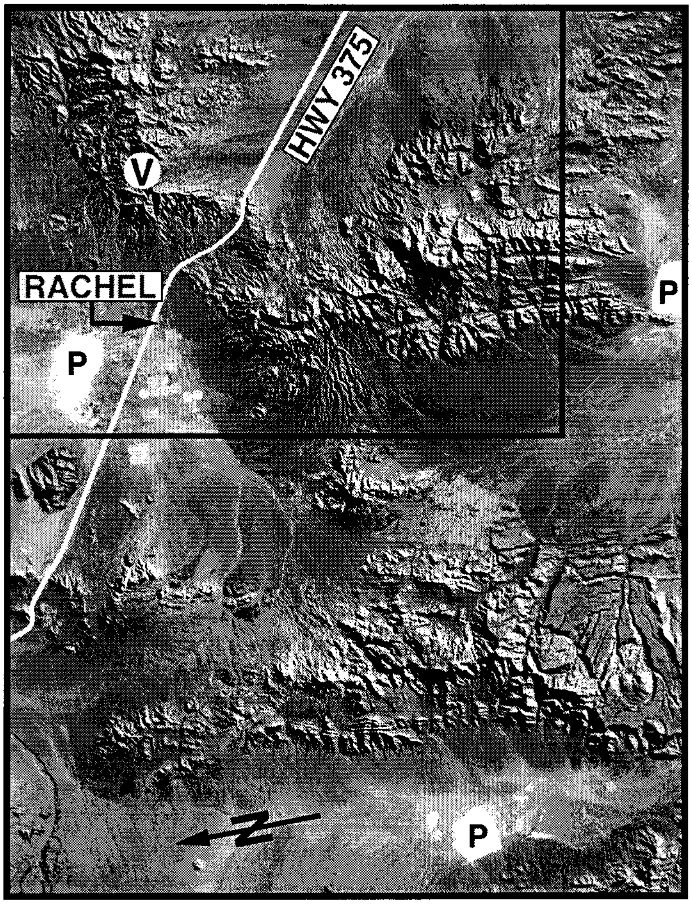


**Figure 1.** Index map derived from Landsat TM band 4 merged with shaded relief from a USGS 30m DEM. This scene matches that of the band ratio images in Figure 3. Total scene area is 52 x 68 km. Town of Rachel, State Highway 375, playas (P), field view site shown in Figure 2 (V), and north arrow are indicated. Black rectangle indicates subscene cropped and rotated for enlarged view of band imagery in Figure 3. Mountains include the Timpahute (upper left), Groom (upper right-central), and Belted (lower right-central) Ranges.

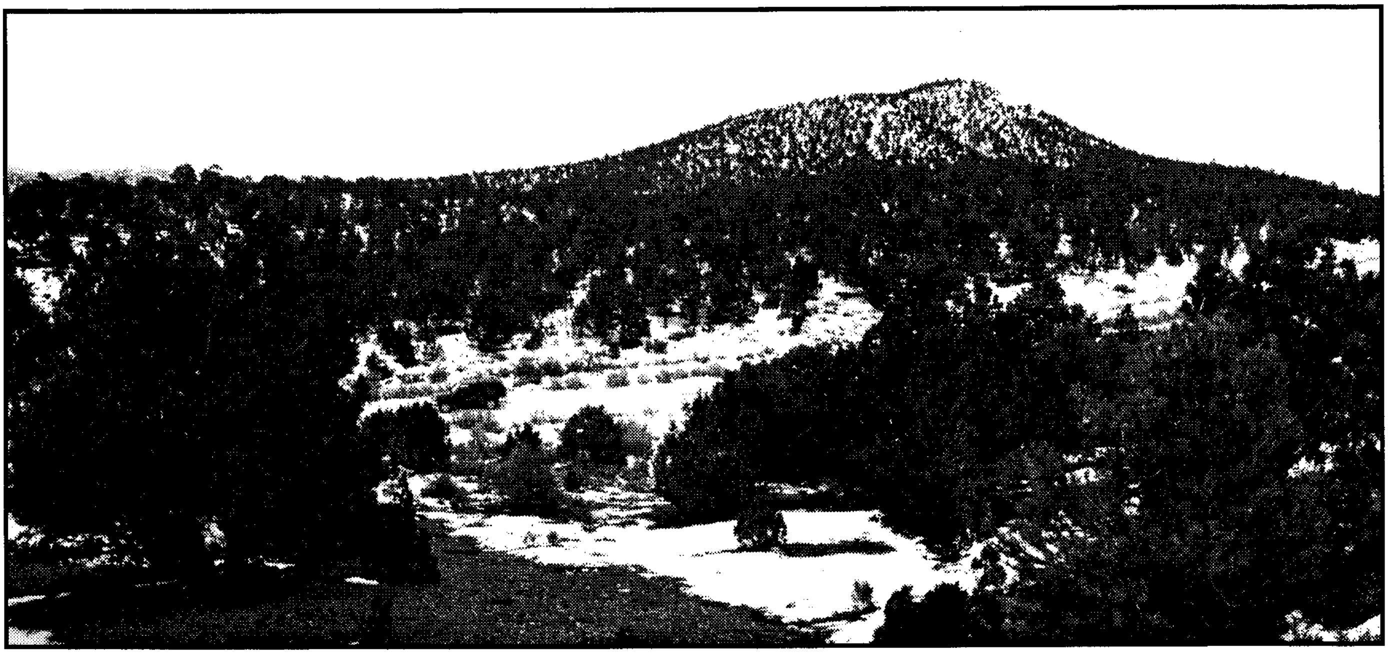

**Figure 2.** Field view in the Timpahute Mountains showing open canopy Juniper-Pinyon woodland. Other ground cover is minimal, except for snow, which was not present during Landsat image acquisition. View southeast. Vehicle at left-center provides scale.

**Figure 3.** Image pairs before and after de-vegetation processing. (A) Band ratios 3/1, 5/4, and 5/7 in blue, green, and red, respectively, achromatically modulated by band 4. (A') Scene de-vegetated via ratio processing. (B) Bands 1, 4, and 7 in blue, green, and red, respectively. (B') Scene de-vegetated via band processing, with saturation enhanced. Band scene is enlarged upper-left part of ratio scene, as indicated in Figure 1, and is rotated clockwise.


A
A'
B
B'

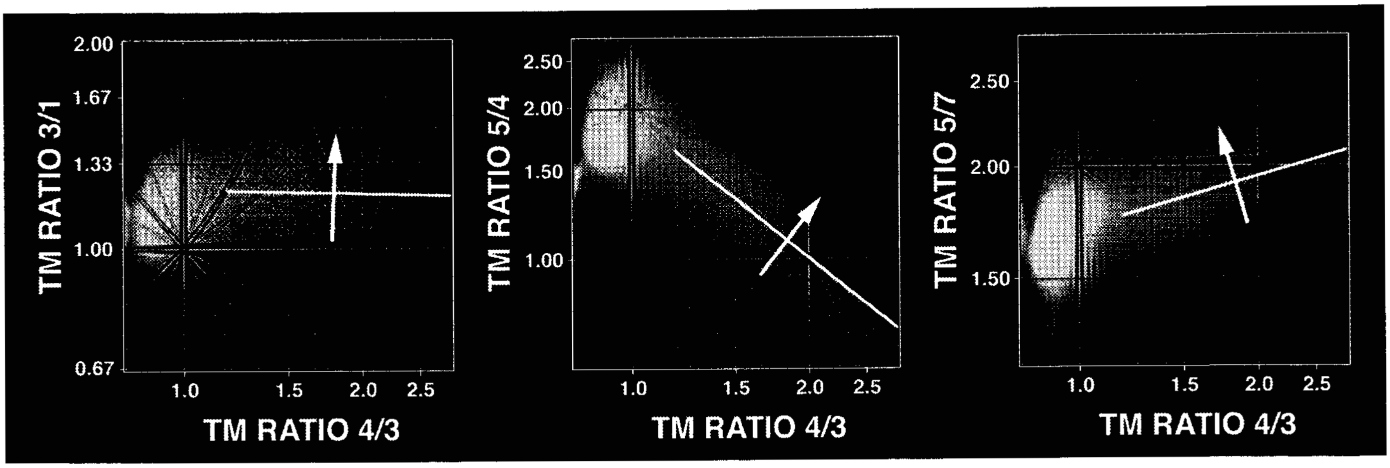


**Figure 4.** Ratio-versus-index plots with logarithmic scaling. Best-fit lines exclude data with TM ratio 4/3 (vegetation index) values of 1.185 and lower. Arrows indicate data re-measurement direction orthogonal to the vegetation trend. See text for explanation of data patterns.

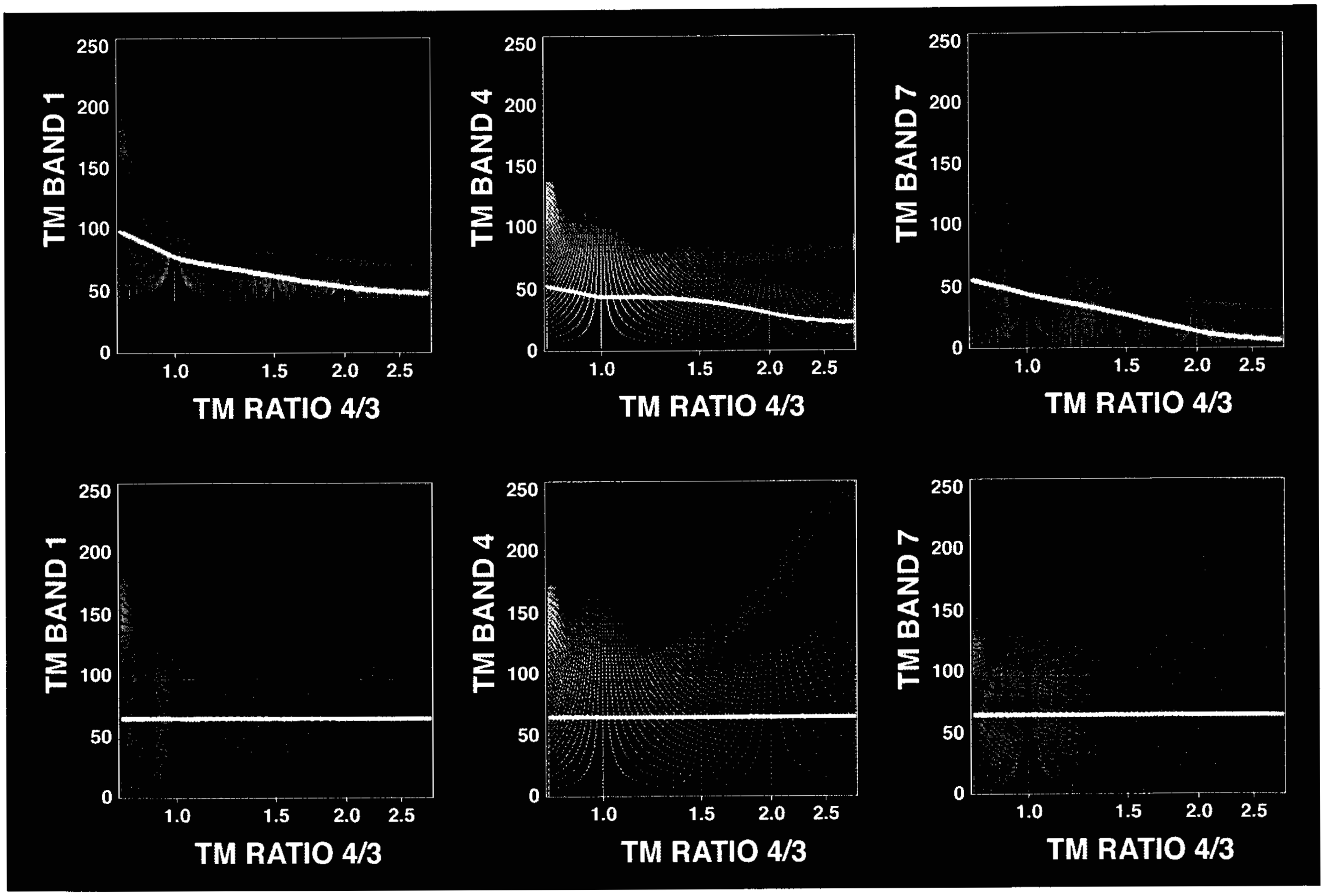


**Figure 5.** Band-versus-index plots. Top: Raw band data plotted against TM ratio 4/3 (vegetation index). Smoothed best-fit lines exclude playa pixels (bright with low index values, at upper left) and alfalfa fields (bright trend with high index values, at upper right). Bottom: Same data after path radiance adjustments and multiplicative scaling of each index column to flatten best-fit line at a constant value of 64.